NEURO-FUZZY SYSTEMS IN ULTRASONIC WELD EVALUATION

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INTRODUCTION

Ultrasonic weld inspections are typically performed manually, which require significant operator expertise and time. Thus, automation of ultrasonic data analysis is an important area of current research in NDE. There is a need for automated data analysis schemes capable of handling imprecise data and providing results in real time. This paper presents a combination of neural networks and fuzzy-logic to automate different aspects of ultrasonic data analysis. Neural networks automate learning, and hence are best used when the relationship between the input space and the output space is highly nonlinear or unknown. The relationship between ultrasonic A-scan signal characteristics and defect class producing the signal is not straight forward. In this work a multi-layer perceptron is used for defect classification. Results form different feature extraction schemes icluding an unique combination of time- and frequency-domain features is presented. Fuzzy-logic automates knowledge representation using a fuzzy rule base. Hence, fuzzy-logic is best applied in situations where a knowledge base exists in the form of IF-THEN rules In this paper fuzzy-logic is applied to accept/reject criteria for weld evaluation. The advantages of using fuzzy-logic over traditional Boolean tree-based algorithms, for this application, are discussed.

AUTOMATED DEFECT CLASSIFICATION

The application of automated imaging and artificial intelligence techniques is recommended with ultrasonic methods to obtain high reliability in the classification and sizing of defects [1]. Automated defect characterization for ultrasonic testing has attracted a wide range of approaches, including pattern recognition schemes [2], adaptive-learning methods [3], expert systems [4], and more recently neural networks (NN) [5]. NNs are ideally suited for ultrasonic flaw classification problems for three reasons: (1) they automatically learn the mapping between their inputs and outputs through examples, (2) they generalize for cases not previously encountered, and (3) they produce classification results instantaneously. The input ultrasonic signal to the NN is usually preprocessed with an objective of enhancing the classification rate and obtaining data reduction. Preprocessing and the NN investigated in this work are described in the following sections.

Preprocessing Scheme

The preprocessor serves to obtain descriptors better suited for classification than the raw signal (e.g., by virtue of invariance to temporal shifts). Another function of the preprocessor is to obtain a reduction in the number of inputs to the NN. However, with the current state of the art in computer technology, the latter purpose of the preprocessor is not a prime consideration in choosing the preprocessing scheme. The preprocessing schemes were chosen based on previously reported success and are reviewed below:

A. Moments of the Fourier transform: the technique of using the magnitude of the first few coefficients of a Fast Fourier Transform (FFT), for preprocessing shear-wave angle-beam ultrasonic signals, has been investigated by D. Berry et al. [5]. The classification rate obtained was poor (50 - 60%) for shear-wave ultrasonic inspection of welds in piping. This study concluded that discarding the phase information resulted in the poor classification rate. However, by using the moments of the FFT for preprocessing normal-incidence compressional-wave ultrasonic signals, L.M. Brown and R. DeNale, reported a 100% classification rate with artificially machined defects [6]. The scheme evaluated in this paper is based on the their work. The preprocessing scheme uses four statistical moments of a FFT of the ultrasonic signal: mean (μ), variance (σ^2), skewness (γ_1), and kurtosis (γ_2):

$$\mu = \mu_1 = \Sigma_k \mid x[k] \mid p(|x[k]|) \tag{1}$$

$$\sigma^2 = \mu_2 - \mu_1^2 \tag{2}$$

$$\gamma_1 = (\mu_3 - 3\mu_1\mu_2 + 2\mu_1^3) / \sigma^3 \tag{3}$$

$$\gamma_2 = (\mu_4 - 4\mu_1\mu_3 + 6\mu_1^2\mu_2 - 3\mu_1^2) / \sigma^4 \tag{4}$$

where,

$$\mu_r = \Sigma_k |x[k]|^r \, p(|x[k]|) \tag{5}$$

$$p(|x[k]|) = |x[k]| / \Sigma_k |x[k]| \tag{6}$$

$$x[k] = \Sigma_n x[n] \, e^{-j2\pi kn/N} \tag{7}$$

B. Envelope estimation: in the time domain, information about the nature of the defect is obtained from the envelope of a rectified ultrasonic signal. D. Berry et al. [5] presented variations of this method, which were used in the Idealyst NN software [7] developed at Karta Technology, Inc. Both these efforts demonstrate good success (> 75% correct classification) for shear-wave inspections of welds. The technique evaluated in this work uses a combination of low-pass filtering, rectification, under-sampling, and mean-subtraction to obtain the preprocessed signal for input into the NN. Figure 1 shows the raw signal and the envelope estimation for a typical ultrasonic signal.

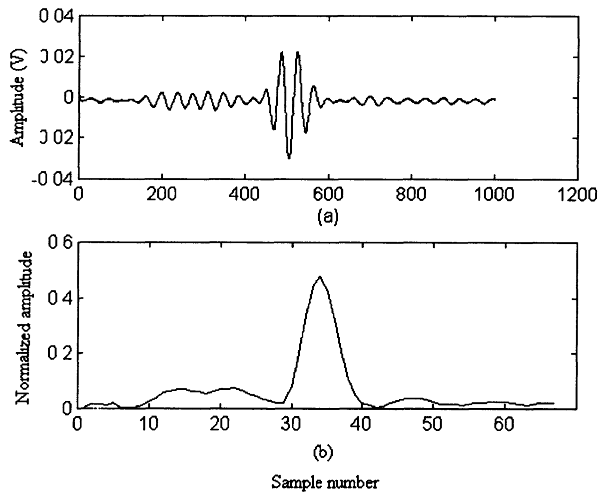

Figure 1. Envelope estimation: (a) raw signal and (b) envelope of zero-mean rectified signal.

C. Principal component analysis: principal component analysis (PCA), a special case of factor analysis, is a mathematical technique used to analyze correlated random variables. PCA finds a linear transformation that produces decorrelated features from measurements available in a signal classification problem. One of the main applications of PCA is the interpretation of multispectral earth resource satellite images. Recently, NDE researchers [8] investigated use of principal components as a preprocessor in defect classification schemes. The transformation to obtain the principal components is of the form:

$$\mathbf{y} = \mathbf{U}'\mathbf{x}. \tag{8}$$

where, $\mathbf{x}$ is the data vector, $\mathbf{U}$ is the transformation matrix and $\mathbf{y}$ is the vector of principal components. The data vector $\mathbf{x}$ is centered by its mean and properly scaled. The transformation matrix $\mathbf{U}$ is composed of the eigenvectors of the variance-covariance matrix $\mathbf{S}$ of data vector $\mathbf{x}$. The vector $\mathbf{y}$ is sometimes called "score," or "latent values"; and the eigenvectors are called "loading vectors," or "latent vectors." As suggested by Jackson [9], it is convenient to rescale the principal components to have unit variance. This is done by dividing the eigenvectors by the square roots of their corresponding eigenvalues. Usually, the original data can be represented by a smaller number of the principal components due to correlation in the data. Therefore only the first few eigenvalues and eigenvectors are used in the PCA model. Two possible approaches to obtaining the principal components are: (1) choosing a representative signal in the dataset against which to compute the variance-covariance matrix of all the other signals, and (2) taking the ensemble statistics and carrying out the PCA computations once. The latter method avoids recalculation of the variance-covariance matrix when dealing with an ensemble of signals with similar statistics. This loses the optimality of individual transforms, but offers an enormous saving in computation.

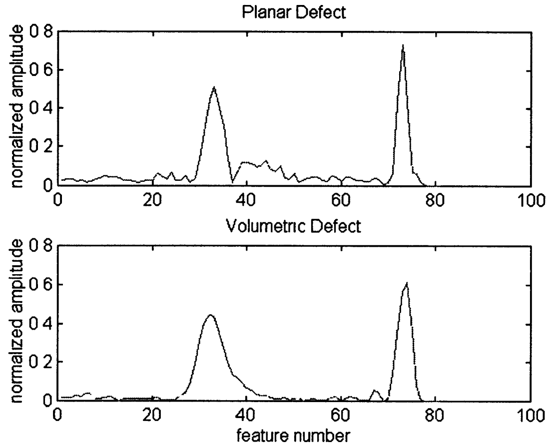

Figure 2. Typical feature vector combining time-domain envelope and the PSD.

D. Combination of time- and frequency-domain information: the features distinguishing different defect classes are observed both in time- and frequency-domain representations. Thus, researchers have investigated the possibility of combining both domain features at the input to enhance classification rate[5, 10]. Figure 2 illustrates the combination of time- and frequency-domain representations used in this project, for representative planar and volumetric defects. This method of combining time- and frequency-domain information is easier to automate than the methods described above. The first 61 feature points were obtained by normalizing a rectified, low-pass-filtered, resampled RF signature from the defect. The last 20 feature points were obtained from the normalized power spectral density (PSD) of the signal. Typically the time-domain signals for planar defects were observed to have faster rise time and a smaller spread in time compared to the volumetric defects. Also, typically planar defects exhibited a smaller spectral spread compared to volumetric defects. Misclassification occurred using either one of these representations when the signal exhibited deviation from the typical behavior. This selected combination of the signal representations reduced the possibility of such misclassifications.

Neural Network Classifiers

The output of the preprocessing scheme is input to a NN classifier. Over the past five years, NN schemes have been applied extensively in defect classification for ultrasonic inspection of weldments [5, 6, 10-12]. They are characterized by having a large number of very simple neuron-like processing elements, a large number of weighted connections between the elements that encode the knowledge of the network, highly parallel distributed control, and an emphasis on automatically learning internal representations. The popularity of NN approaches are due to their speed, robustness, and ability to generalize. These capabilities are derived from the nonlinearities embedded in the nodes of the NN and the large number of connections between nodes. The MLP architecture with the backpropagation training algorithm is the most successful candidate in defect classification, and was used in the current work.

Table 1. Comparison of preprocessing schemes.

Preprocessing Scheme	*Classification Rate (%)*	*Order of Iterations*	*Robustness*	*NN size*
Raw signal	≈ 60	Hundreds	Fair	1000-4-2
Moments of FFT	≈ 60	Thousands	Poor	4-3-2
PCA	≈ 65	Hundreds	Fair	5-6-2
Envelope Estimation	≈ 70	Hundreds	Good	61-4-2
Time and Frequency	85	Hundreds	Good	81-4-2

Comparison of Performance

A comparison of performance of the NN classifier with different preprocessing schemes, is listed in Table 1. The performance with the raw signal is also included for comparison. In all the cases the NN classifier used was the MLP. The nonlinearity used was a hyperbolic tangent function, error goal was 0.01, and learning rate was adaptive. From a total of 39 A-scan signals collected, 20 were used for training, and 19 for testing the NN. The combination of time- and frequency- domain features, developed in this work, provided the best classification rate of 85%. The poor performance of the moments of FFT can be attributed to the possibility that, for shear-wave weld inspection, the phase of the FFT contains information vital for class discrimination, as concluded by D. Berry et al. [5] and D. Birx et al. [12]. Also, with PCA, the use of bulk transformation, loses the optimality of individual transformation, and is possibly an explanation for the low classification rate. Using individual transformation matrices for each signal resulted in too few significant principal components and a consequent non-convergence of the NN. This is consistent with the findings in [6].

AUTOMATED WELD EVALUATION

All discontinuities detected during an ultrasonic inspections are not detrimental to the weld safety. It is not feasible to discard all weld sections that indicate the presence of discontinuities. Hence, methods of determining if a discontinuity is to be regarded as a critical defect, necessitating either repairs or replacements of the weld section, must be developed. The Navy currently uses the NAVSEA 3010 [13] acceptance/rejection criteria, which is a Boolean tree-based algorithm incorporating heuristic knowledge regarding seriousness of defects. The flow diagram of the NAVSEA 3010 acceptance criteria for Class I (full penetration butt welds and corner welds) is presented in Figure 4.

In this work, the acceptance criteria was implemented using a fuzzy-logic inference scheme (Table 2). Fuzzy logic is a convenient way of mapping an input space

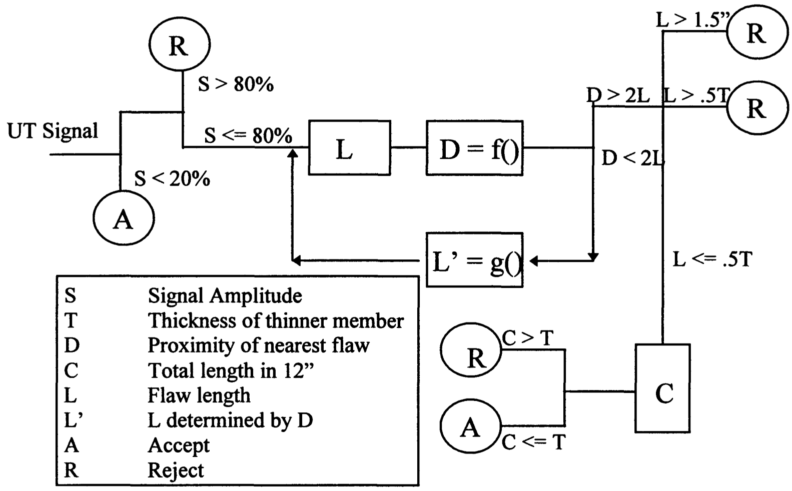

Figure 3. NAVSEA 3010 acceptance criteria for Class I welds.

Table 2. Rules used in the fuzzy inference system.

1. If (amplitude is ARL) then (decision is reject)
2. If (amplitude is DRL) then (decision is accept)
3. If (amplitude is INT) and (length is long) then (decision is reject)
4. If (amplitude is INT) and (length is short) and (total is large) then (decision is reject)
5. If (amplitude is INT) and (length is short) and (total is small) then (decision is accept)

to an output space. The main advantages in using fuzzy logic for NAVSEA 3010 acceptance criteria are: fuzzy logic can be built on top of the experience of experts, fuzzy logic is based on natural language and hence conceptually easy to understand, all rules for the system are considered in parallel for the decision process hence the system is more robust, and information regarding the defect condition (in addition to the accept-reject decision), is obtained.

The algorithm tested has five rules (obtained from the NAVSEA 3010 acceptance criteria), as given in Table 2, and three inputs, amplitude of the signal, measured length of the flaw and total length of flaws in 12 inches. Other parameters described in NAVSEA 3010 are factored out in the preprocessing. The output is an indication of the seriousness of the flaw. The amplitude is divided into three fuzzy membership functions: (1) disregard level (DRL), (2) intermediate level (INT) and (3) amplitude reject level (ARL). Similarly, the length has two membership functions, long and short; and the total length has two membership functions, large and small. Also, the output has two membership functions, accept and reject. The membership criteria is based on the NAVSEA 3010, with the boundaries of membership having some degree of fuzziness. The final output is a de-fuzzyfied number between 0 and 1 indicating the seriousness of the flaw. The scheme has been tested for different input parameters from actual tests and provides results consistent with the NAVSEA 3010 acceptance criteria, with added information on the seriousness of the flaw.

SUMMARY

This work demonstrated the use of neural network and fuzzy-logic technologies in appropriate aspects of ultrasonic weld evaluation. The use of an NN scheme for defect classification was successful and is recommended for the real time weld inspection system. A classifier using a MLP with an input consisting of the UT signal's PSD appended to the corresponding time domain envelope is endorsed based on results obtained. Two issues associated with a NN classifier which need to be adressed for enhancing its reliability: (1) The NN classifier could misclassify if presented with data obtained using a different transducer (frequency, angle, and active-element area) during testing than that used to obtain the training data. Hence, advanced research is required to design invariance transformations for making the ultrasonic signal invariant to transducer parameters. (2) Occasionally the A-scan signal obtained from the defect contains wave-forms other than those due to reflections off the defect. These could include converted modes and tip diffracted signals. Hence, advanced research is required to develop intelligent methods of extracting only the signal reflected off the defect.

The use of fuzzy-logic adds value to the acceptance criteria used in weld evaluation. Issues requiring further research, with regard to the acceptance criteria, are related to the use of signal amplitude and defect length in NAVSEA 3010. Researchers concluded that both these parameters should be avoided as factors influencing weld evaluation [14]. The amplitude of the signal may be influenced by many parameters other than the size of the reflector such as roughness, transparency, and orientation of the defect and the effectiveness of ultrasonic coupling. Also, the most important defect dimension is its height. Though crack height and length have a general relationship, it is not consistent enough to provide a basis for quantitative inspection in majority of cases. Advanced research is recommended to modify the weld evaluation criteria to reflect current understanding of ultrasonic testing.

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